Combatting forest fires in arid Sub-Saharan Africa: Quasi-experimental evidence from Burkina Faso

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Abstract

Forest fires have been identified as one of the main drivers of deforestation and forest degradation Sub-Saharan Africa. We study the (short-run) effects of a program targeted at reducing the incidence of forest fires in 12 gazetted forests in arid Burkina Faso. Making use of detailed satellite images on forest fires and remaining vegetation cover in, in total, 78 forests over the period 2014-2018, we estimate the the average treatment effect of the intervention using the Synthetic Control Method. We find that the intervention resulted in a significant decrease in (the severity of) forest fires in the periods where forest fires tend to be most prevalent – at the end of the agricultural season (in November), and at the onset of the new agricultural season (in March). However, these estimates are likely to be partially driven by imperfect fitting on pre-treatment outcomes. We find mixed evidence on the extent to which this resulted in increased vegetation cover.

Keywords: `Burkina Faso, forest conservation, bush fires, forest cover, synthetic control method`

☆The current paper is a draft and is subject to changes. All errors remain our own.

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1. Introduction

Forests provide a number of local and global ecosystem services including carbon sequestration, biodiversity conservation, local climate regulation (especially precipitation), and soil and water conservation. Deforestation is a concern especially in arid zones, because of the relatively high rates of deforestation and because forest loss may give rise to desertification. As part of the Kyoto Process the United Nations have initiated a global forest conservation policy, the Reduction of Emissions from Deforestation and forest Degradation (REDD+) Program, that provides not only technical assistance but also financial compensation to developing countries if they manage to improve forest conservation as compared to a baseline (or business-as-usual) scenario. To learn how to overcome the many challenges and constraints that are associated with implementing forest conservation programs, the Climate Investment Fund (CIF) has selected eight developing countries as pilot areas to assess the effectiveness of the interventions and to identify the main barriers hampering successful implementation of the interventions in the field. Burkina Faso, the country this IE program will focus on, has been chosen as the pilot country for the arid and semi-arid areas.

In this paper, we assess the effectiveness of an intervention, funded by the CIF and implemented by the government of Burkina Faso, aimed at reducing one of the main causes of deforestation in the country – forest fires. The government's intervention targets 12 of Burkina Faso's 77 gazetted forests, and consists of a variety of measures – setting up fire barriers to compartmentalize wildfires, but especially raising awareness among the local populations about the detrimental effects of forest fires. Most of the forest fires in Burkina Faso are human-induced, aimed at clearing land and increasing soil fertility. But there is a religious component to the end of the agricultural season's burnings too.

We use the synthetic control method on satellite-based measures to estimate the program's impact on forest occurrence and vegetation cover. These measures on the 77 forests are compiled from accessible data in the MODIS and LANDSAT 7 databases. We aggregate forest fire measures to the forest-month level, while NDVI and EVI measures on vegetation cover are aggregated to the forest-season-level. The resulting panel dataset covers the period from June 2004 until October 2018. Non-exogenous selection of forests along potentially time-varying factors is taken into account in the synthethic control method. For each treated forests it creates a convex linear combination of non-program forests which fits on the observed pre-program outcomes of the selected forests. We compare the outcomes of program forests to those of the synthetic during the program period, since the synthetic control's outcomes serve as estimates of the counterfactual.

Our main results show that the number of forests fires decrease in November and March in response to the program. In November, the beginning of the dry season with most of the fire occurrences, the reduction is between $50 - 30\%$ when compared to fires in the dry-season before the program. Although absolute decrease in March is a magnitude smaller, in relative terms the effect is similar to that in November. These reductions seem to be driven by a lower number of burned areas, which reflects that there are less uncontrolled fires or that they are extinguished more efficiently than before the program. However, these results must be regarded with a grain of salt as the synthetic controls do not seem to perfectly track the treated forests before the program. Imperfect fitting is not present when estimating the impacts on vegetation, but results do not suggest that reduced fire occurrence translated into more intense vegetation cover.

The remainder of this paper is organized as follows. Section 2 contextualizes forest degradation and forest fire occurrence in Burkina Faso and present the FIP program. Data sources, data processing and the final variables are discussed in section 3. Section 4 details the estimation procedure of the synthetic control method. Results are in section 5, while we provide discussion and conclusion in section 6.

2. Study context of Burkina Faso

2.1. Geography and climate of Burkina Faso

To understand the potential impact of the government's intervention on forest fires, let us first introduce the relevant climatological conditions of Burkina Faso. The country is located in the transition zone between the Sahelian and the Sudanian climate zone in West-Africa (Ministry of Environment and Sustainable Development, 2014). Most of the country falls into the Sudanese zone, with average rainfall of between 600 and 1000 mm and with about $50 - 100$ rainy days. Vegetation cover consists of wooded and arboraceous savannas. The north of the country falls into the Sahellian zone, with < 600 mm of average annual rainfall and with less than < 45 days rainy days. The natural vegetation in this zone consists predominantly of grass savannahs with shrubs and sporadic tree cover.

In general, the country has a dry tropical climate with four seasons (Somé et al., 2013), but the climate allows for only one agricultural season.[3] The rainy season starts in May-June, and this marks the start of the agricultural season as most of the annual rainfall is concentrated in this time period (FAO, 2014b). August-September is characterized by decreasing rainfall and temperatures, and the growing season typically ends in October-November. The dry and cool season then lasts from November-December until February-March, followed by the hot season as the *harmattan* winds blow from the Sahara. This period from February until March-May is considered to be the off-season to growh and harvest rice and sorghum (FAO, 2014b).

2.2. Forest degradation and causes of forest fires in Burkina Faso

Annual deforestation rate in Burkina Faso between 1990 and 2010 was 1.1%, despite the government's continuous effort to tackle deforestation and forest degradation since the 1980s. In this period, the share of forests in land areas dropped from 46% to 39% , resulting from forest losses in clearly defined forests and other wooded lands such as wooded savannas, dry, and gallery forests (FAO, 2014a). The main causes of these changes are identified to be the expansion of agricultural and pastoral activities, forest clearing for firewood or charcoal, and the prevalence of bush and forest fires (Pouliot et al., 2012; CIFOR, 2016). Expansion of agricultural and pastoral activities is mainly related to the increasing population pressure from population growth and from intra-country migration from the Sahelien areas in the north towards the more productive areas in the tropical forest regions (Pouliot et al., 2012; Ouedraogo et al., 2009). Since agricultural intensification in rural areas is hindered by inequality of assets and wealth, most notably land rights (Goldstein and Udry, 2008; Etongo et al., 2015), more lands are cleared to meet the increasing demand for agricultural products (Ouedraogo et al., 2011). Pressure from increasing population also affects demand for firewood and charcoal which are the most affordable energy sources for low-income, rural households (Ouedraogo, 2006; Bensch et al., 2015; Ouedraogo et al., 2011).

Forest fires are also anthropogenic, but only partially related to population pressures. Although fire setting in forests is criminalized since the 1980s (Devineau et al., 2010), forest clearing for agricultural or pastoral purposes can be carried out by intentionally setting clearing fires. Also, herders burn

[3]We define the agricultural year to start from the beginning of June until next June, aligning the beginning of the growth season (FAO, 2014b). That is the 2014 agricultural year lasts from June 2014 until June 2015.

the lower levels of the forests in the dry season to facilitate faster regrowth of grasses that their herds can graze (Savadogo et al., 2007). Additionally, hunters and poachers set fires to lure out preys and improve visibility in the hunting territories Sawadogo (2009). Fires are also present on agricultural plots (where they are set to clear old fields after the growth season and to manage soil fertility), and can spread to forest. All these fires are initially smaller and affect the lower vegetation; prevent the development of sapling, canopy in growth; and killing seeds (Zida et al., 2007).[4] They can directly damage already grown tree canopy if they intensify and spread in the forests, since these fires are not lit under controlled conditions. Low intensity, controlled early fires on the other hand are set to reduce the amount of fuel for more hazardous late fires and to create firebreaks that prevent the spread of late fires. Due to policies since the 1980s religious fires[5] are organized at the community level and are supervised by relevant forest management authorities, thus these types of burnings became controlled (Devineau et al., 2010). All these controlled fires are carried out by forest management agencies and scheduled for October-November, the beginning of the dry season when the vegetation to be burned is not dry (Savadogo et al., 2007).

2.3. The Forest Investment Project in Burkina Faso

As indicated, the Forest Investment Project (FIP) is Burkina Faso's initiative to support the international REDD+ strategy. Although not selected to be an initial partner country in the REDD+ initiative, the Climate Investment Funds selected Burkina Faso as one of the pilot developing country for its Forest Investment Program given how representative it is of arid and semi-arid areas and given its past conservation efforts (i2i DIME, October 2016).

Conservation efforts in the Burkinabe FIP program centers on 12 gazetted forests, which were selected from the set of Burkina Faso's 77 gazetted forests in two stages (see fig. B.1). In the first stage, the gazetted forests were ranked on the the perceived urgency of conservation, where perceived urgency was

[4]Besides, fires can lead to a biome dominated by fire-resistant plants (Sawadogo, 2009; Devineau et al., 2010). This generally limits the types of non-wood forest products that becomes available for communities around the forests.

[5]These religious and culture fires can serve different purposes depending on the traditions of the community. They can be used to eliminate weeds and pests in the areas around holy sites (Dugast, 2008; Daugey, 2016). Other ritual fires are lit to ward off harmful spirits (Issaka and Ouedraogo, 2011). In other cases, customary fires are symbolic. For example, they might reflect regeneration (Luning, 2005; Dugast, 2008)

based on wildfire incidence, deforestation and ecosystem degradation, as well as on carbon sequestration capacity. This reduced the number of candidate forests from 77 to 23. Because of budget concerns a second stage was implemented, which consisted of selecting 12 out of the remaining 23 gazetted forests based on forest size, the presence of a forest management system, and on the (perceived) availability of non-timber forest products.[6] Although the 11 forests excluded in the second stage are fairly comparable to the selected 12 forests along the first set of criteria, this implies none of the excluded forests from the first nor the second stage are directly comparable to the final 12.

Burkina Faso's FIP pilot program was scheduled to run from October 2014 to 2018, and consisted of two main projects. The first project, implemented by the African Development Bank[7], focuses on the improving vegetation cover and forest conservation in the selected gazetted forests by eliciting conservation efforts from neighbouring communities. These efforts are strengthened by financial incentives to communities and by improving forest governance at forest and community level. The second project from the World Bank[8] targets tree conservation in the areas surrounding the selected gazetted forests. This project operates through knowledge transfer, technologies, infrastructures, and land use plans that generate income sources for communities that are compatible with conservation efforts.

More directly related to forest fires, the program intended to raise awareness at the local level, transfer additional knowledge to forest management agencies to better deal with forest fires, provide them sufficient material assets to monitor and prevent fires, open firebreaks in and around forests to limit expansion of burning fires, and offer payment-for-ecosystem contracts to communities conditioning on the number of fire occurrences. Only knowledge transfer to forest management agencies was potentially implemented in time due to delays in the program, while the rest (along with other forest conservation measures) are implemented from late 2016-early 2017. Hence we potentially measure the effect of improved forest management activity.[9]

[6] The two lists of exact criteria are presented in appendix Appendix A.

[7] The project is titled as "Gazetted Forest Participatory Management Project for REDD+".

[8] The project is titled as "Project for the Decentralized Management of Forests and Wooded Areas".

[9] This potential channel can be closely linked to a previous project implemented by the Burkinabe government and financed by the Finnish government between 1998 and 2006. The Fire Management Project relied on a community-based approach that provided basic knowledge on fire management to villages and improved local institutions (e.g. by

3. Data

The analysis in this paper relies on panel of monthly grid-level data on forest fire occurrences and vegetation cover from 2000 to 2018 in Burkina Faso's gazetted forests. Similarly to Burgess et al. (2012), we use measures extracted from satellite images that are made available by NASA and USGS. To be able to better understand the data and its limitation, we discuss the sources of these variables in more detail.

Satelite based data on forest fires are collected from the FIRMS database.[10] More specifically, we use fire data from the MODIS collection in FIRMS which has data from November 2000, rather than the VIIRS collection in FIRMS that is only available from 2012.[11] Both dataset determine forest fire occurrence based on infrared radiation, but they are based on different satelite images and processing algorithms. Having a longer panel allows us to observe fire occurrences years before the program, which is important as we are estimating the effect of the program using a difference-in-difference approach.

Using the MODIS dataset comes at the expense of slightly less frequent observations and lower precision regarding the location of fire occurrences. That is, the satellite for the MODIS has a global coverage over 1-2 days and the observations are assigned to 1 km pixels, whereas the satellite from the VIIRS collection has a global coverage at every 12 hours giving data on 350 m or 750 m large pixels (NASA, 2019).[12] Having less accurate location on the fires is not restricting our analysis as the estimation strategy does not exploit this information.[13] However, a wider time window for global

setting Fire Management Committees in 1999). If villages and local forest agencies are aware of these knowledge, but their effort diminished after the end the Fire Management Program, then learning about the objectives of FIP program in the 12 selected forests village residents and forestry agencies might decide to increase their fire management efforts even before any related FIP component was implemented. In this case, one would measure the effect of announcing the program before the implementation of any program component.

[10]FIRMS stands for Fire Information for Resource Management System and it is collected by NASA.

[11]MODIS stands for Aqua Moderate Resolution Imaging Spectroradiometer, while VIIRS stands for Visible Infrared Imaging Radiometer Suite.

[12]Time for having global coverage means the time the satellite needs to collect data over the whole globe. This is not the same time the satellite takes to return over the same area. Within one cycle of global coverage the satellite passes over the same area while not covering some part of the globe. Both satellites take 3-4 images of the same area on the day in which the area is covered by the orbit of the satellite (NASA, 2019).

[13]Also this pixel size is small enough to get an idea about the presence of firebreaks and the

coverage means that the MODIS dataset might not cover some fires that occurred during days the satellite did not fly over Burkina Faso.[14] In this case, the dataset indicates zero fire occurrence for the grid on that day. The extend of this issue is not explored further at this stage of the analysis. The MODIS collection only indicates the day at which a forest fire is detected and the grids which were affected by the fire. This implies that our final dataset will have 0 fire occurrences for those grids on which no fire was detected.

Using the data from the MODIS dataset, we construct three monthly forest fire occurrence measures that take into account the uncertainty from the fire detection algorithm. The confidence level between 0 and 100% is available for each detected fire. To check whether including potentially false positive detection affects results, we use the number of all fire occurrences (`fire`), the number of fire occurrence with at least 50% confidence(`conf50`), and the number of fire occurrence with at least 80% confidence (`conf80`) per month-grid as outcome variables.[15] These variables capture the average number of fires that burned on the grids of the forests in the particular month. The three variables are illustrated in fig. C.2a-C.4a. The figures indicate that fires occur mostly in the dry season (November-February), and not at all in the rainy season. To provide approximate information on the size of the area affected by fire, we also regard at the forest-month-level the share of grids that were affected by fire.[16]. The corresponding monthly time series are presented in fig. C.2b-C.4b.

The other set of outcome variables is grid-level vegetation cover which is expected to reflect any potential impacts on forest cover, similarly as in Foster and Rosenzweig (2003). In this dataset, there are two measures on

occurrence of controlled burnings intended to create firebreaks. Plotting the number of fires on a map for each grid for a given month, firebreaks can be spotted by straight lines which have a consistent number of fire occurrences on one side and no fire occurrences on the other side.

[14]To verify whether this is a significant issue one can compare fire occurrences between the MODIS and VIIRS datasets. To do so, one has to aggregate forest fire occurrences at comparable forest grids.

[15]Note that low thresholds for confidence level might lead the under-rejection of false fire detections, while high thresholds might result in over-rejection of true, but imperfectly observed fires. Also note that less intense fires are more likely to be falsely rejected at a higher threshold.

[16]Obviously, this provides an overestimate of the area burned, as not all vegetation on a grid may have been consumed by fire. However, the size of the pixels is sufficiently small for the estimate the be quite precise (Burgess et al., 2012; NASA, 2019).

vegetation cover: the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index Data (EVI).[17,18] The measures are available from the LANDSAT 7 database.[19] Up until February 2013 observations were collected by just one single satellite with global coverage of 16 days. The addition of a second satellite reduced increased the subsequent frequency of global coverage to once every 8 days. Since under normal conditions the vegetation cover changes at a slower rate than forest fires, the lower frequency of satellite imaging mostly causes a problem in periods of increased cloud cover – that is, in the rainy season.[20] Figure C.5 presents the share of forests with missing NDVI values over time. It shows that the NDVI data are largely missing in the period June-September. That means that we can only compare vegetation cover in the treatment and control forests in the remainder of the year, when forest fires are also more likely to occur.

Missing values in the vegetation cover indices generate two potential problems. First, they can bias our estimates if there are systemic differences in cloud coverage over treatment and control forests that we are not accounting for. The second problem is related to our main identification strategy that requires a strongly balanced panel at the forest level. To work

[17] NDVI, the Normalized difference vegetation index, reflects the relation between red visible light (RED, which is typically absorbed by a plant's chlorophyll) and NIR wavelength (which is scattered by the leaf's mesophyll structure) (Glenn et al., 2008)). The NDVI is calculated as (NIR-RED)/(NIR + RED). EVI, the Enhanced Vegetation Index, has been designed to improve the sensitivity in high biomass regions reducing the atmosphere influences, especially in areas of dense canopy which uses the blue band to correct aerosol influences in the red band, showing photosynthetically active vegetation (Huete et al., 1994, 1997, 2013). It is calculated as: G * ((NIR - RED)/(NIR + C1 * RED - C2 * BLUE + L)), where coefficients are adopted from the MODIS-EVI algorithm indicating the gain factor (G = 2.5), the adjustment for correcting differential, red radiant and non-linear transfer through canopy (L = 1), and the aerosol resistance term which corrects atmospheric influences in the red band (C1 = 6 and C2 = 7.5). EVI adjustments are designed to make EVI more robust than NDVI in areas with high soil exposure and in dense vegetation, but also more sensitive than NDVI to variation in the viewing geometry, surface albedo, and sun elevation angle across variable terrain (Garroutte et al., 2016). For more information, see (Adjognon et al., 2019).

[18] At this stage of the research we do not use machine learning techniques on NDVI or EVI measures to catogerize grids on whether there is still forest cover or not, like in Burgess et al. (2012) or Jayachandran et al. (2017).

[19] The exact data source is LANDSAT 7 Collection 1 Tier 1.

[20] To see the extent of the problem, one can navigate to the source of the dataset (Earth Engine Data Catalog, *last. accessed April 14, 2019*) and run the example code in the corresponding code editor, setting the date between June 1, 2010 and August 1, 2010 and centralizing the map on Burkina Faso (`Map.setCenter(-1.98,12.27,7)`).

with the remaining data, we first impute the missing forest-month vegetation indices for the non-rainy season months separately for NDVI and EVI. We replace missing values with the mean of observed vegetation indices of other forests in the same treatment group in the same month. We then define three periods within the agricultural year, and average the vegetation indices within these periods for each forest. The periods are chosen to reflect the seasonal changes: (1) the post-rainy season's transitory period covering September-October; (2) the dry period from November to February; and (3) the pre-rainy season's transitory period from March until May. Imputing missing months and averaging observations in these periods, we get data points that combine observable values and imputed values to characterize the period in question.[21] The result is an annual panel for forests with 6 variables capturing vegetation cover in different periods of the year: 3 for NDVI and 3 for EVI. The corresponding time series are presented in fig. C.5a-C.5c. In addition, fig. C.5d-C.5f and fig. C.6a-C.6c present similar time series of periodical forest fire occurrences and share of burned forest grids (with no restriction on the confidence level of forest fire detection).

4. Empirical approach

The Synthetic Control Method (SCM) has been developed to generate treatment effect estimates that are unbiased even when unobservable variables driving selection into treatment vary over time (Abadie et al., 2010; Cavallo et al., 2013). The exact criteria on the basis of which treatment forests were selected are unknown and are potentially time-varying, but SCM seems to be particularly well-suited for our purposes because of the arguably high serial correlation in the (unobservable) selection variables. The underlying idea of SCM is to estimate the counterfactual outcomes for the treatment forest (had they not been treated) by taking a weighted average of the outcomes of a selection non-treated forests. The method assigns weights to all 65 gazetted non-treatment forests OR IS IT 11 – = 23-12? (of the 77 in the country – all gazetted forests that were not selected for the intervention) – zero, or a positive weight – such that the weighted average of the set of control forests traces the treatment forests' pre-treatment trend (the number of

[21] We also present estimation results without imputing and dropping forests where any of these periodical values are missing. Dropping forests only affects 1 treated forests for pre-rainy season NDVI and EVI measures and we are still left with more than 50 non-treated forests. Given extensive missing values, we are not able to estimate effects on vegetation cover in the post-rainy season.

forest fires in each period, or the NDVI index) as closely as possible. More specifically, the algorithm chooses the convex linear combination of non-treated forests that yields potential pre-treatment outcomes and covariates that are closest to those of the corresponding treated unit. Abadie et al. (2010) shows that when the synthetic control closely fits pre-treatment outcomes and observed covariates to those of the treatment unit, unobserved confounding factors will also closely fit and the post-treatment outcomes of the synthetic will provide unbiased estimates on the treated unit's missing counterfactual outcomes.

To present the estimator, the estimation procedure, and the inferential procedure of this method more formally, we follow Cavallo et al. (2013). Assume that there are I treatment units (indexed $k = 1, .., K$) which are continuously treated from $T_0 + 1$ until T $(1 \leq T_0 < T)$, whereas there are J non-treated units (indexed $j = 1, .., J$) are never treated in the time period under consideration $(t \in \{1, ..T_0, ..., T\})$. Let us use Y_{it} to denote the observed (or actual) outcome of unit i in period t, and Y_{it}^I and Y_{it}^N the outcomes of unit i in period t had it been treated, or not treated, respectively. Obviously, for treatment forests $Y_{it}^I = Y_{it}$ while Y_{it}^N is unobserved. The reverse holds for the potential control forests. Using an indicator variable D_{it} to capture whether unit i is treated in period t, we have

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it},$$

where $\alpha_{it} \left(= Y_{it}^I - Y_{it}^N\right)$ is the treatment effect in forest i if it is exposed to treatment in t (identical to the Rubin Causal model). Given the observable data at hand, we intend to estimate the treatment effects in $T_0 < t \leq T$ for unit $i \in I$. Since only the treated outcome is observable for i in this period and $\alpha_{it} = Y_{it} - Y_{it}^N$ for $t > T_0$, we need to estimate the counterfactual outcome in this period, Y_{it}^N.

Abadie et al. (2010) suggest using a weighted average of non-treated units to estimate the missing counterfactual. We can capture each potential synthetic control with $\boldsymbol{W_{(J\times 1)}} = (w_1, \ldots, W_J)'$, a vector of non-negative weights summing up to one that assigns weight w_j for the corresponding unit $j = 1, ..., J$. If we also have a vector of observable covariates ($\boldsymbol{Z_i}$) that affects the outcome and are not affected by the treatment, the ideal synthetic control would fit pre-treatment outcomes and the relevant observable outcomes of the treated unit:

$$\sum_{j=2}^{J} w_j^* Y_{jt} = Y_{kt} \text{ for } 1 \leq t \leq T_0; \qquad \sum_{j=2}^{J} w_j^* \boldsymbol{Z_j} = \boldsymbol{Z_k} \quad \forall\ k = 1, ..., K. \quad (1)$$

Fitting on the pre-treatment outcomes as well as on observed covariates (those which are expected to affect the outcome variable of interest), the authors show that the synthetic control also fits the unobserved relevant factors of the treated units. In this case, the missing counterfactual outcomes of the treated unit could be estimated by the outcome of the synthetic control and an unbiased estimate of the treatment effects would be:

$$\hat{\alpha}_{kt} = Y_{kt} - \sum_{j=2}^{J} w_j^* Y_{jt} \quad \text{for } T_0 < t \leq T \;\wedge .\; \forall\, k = 1, ..., K. \tag{2}$$

Perfect fitting on pre-treatment outcomes and relevant observable characteristics (eq. (1)) is possible when these attributes of treated unit k are in the convex hull of the attributes of non-treated units. That is if

$$(\boldsymbol{Y}_{k,t<T_0}, \boldsymbol{Z_1}) \quad \in \quad \mathrm{Conv}\left(\left\{(\boldsymbol{Y}_{j,t<T_0}, \boldsymbol{Z_j})\,,\; \forall j = 1, ..., J\right\}\right).$$

In the actual algorithm, weights ($\boldsymbol{W}_k$) are estimated such that the synthetic control fits those attributes as well as possible for the corresponding treated unit k. Denoting by $\boldsymbol{X}_k$ a $(m \times 1)$ vector of the attributes of the treated unit k need to be matched, and by $\boldsymbol{X}_0$ the corresponding $(m \times J)$ matrix collecting the attributes of the non-treated units, Abadie et al. (2010) propose to obtain the optimal weights by minimizing the following distance for all $k = 1, ..., K$:

$$\min_{\boldsymbol{W_k}, \boldsymbol{V_k}} \; \| \boldsymbol{X}_k - \boldsymbol{X}_0 \boldsymbol{W}_k \| = \sqrt{(\boldsymbol{X}_k - \boldsymbol{X}_0 \boldsymbol{W}_k)' \, \boldsymbol{V}_k \, (\boldsymbol{X}_k - \boldsymbol{X}_0 \boldsymbol{W}_k)},$$

$$\text{s.t.} \quad w_k, j \geq 0 \;\; \forall\, k = 1, ..., J \quad \wedge .\; \sum_{j=1}^{J} w_{k,j} = 1.$$

Here $\boldsymbol{V}_k$ is a $(m \times m)$, symmetric, and positive semi-definite matrix that affects mean square prediction error by weighting the m attributes on which the synthetic control is fitted. After estimating the effect for each treatment period and for each treated forests, the algorithm averages the observable outcomes over treated forests ($\frac{1}{K}\sum_k Y_{k,t} = \bar{Y}_t$) and compares this time series to the average of corresponding synthetic outcomes ($\frac{1}{K}\sum_k \sum_j \hat{w}_{k,j} Y_{j,t} = \hat{Y}_t^{\mathrm{SC}}$). We report these averaged treatment effects for each post-treatment period.

We use every pre- and post-treatment periods to compare observed outcomes of treated forests and the estimated counterfactuals from SCM. However, when working with monthly fire occurrences or burned grids variables, we limit the estimation of forest and attribute weights ($\boldsymbol{W}$ and $\boldsymbol{V}$) on part of the pre-treatment period (from June 2006 until September 2014[22]) due to computational limitations. This is not the case when we use vegetation cover measures since these estimates rely on annual data. Regarding the set of attributes ($\boldsymbol{X}$) used for constructing the control group, we include all the outcome variables for these pre-treatment periods discussed above, as well as forest size[23], the average number of fire occurrences on a forest grid over the pre-intervention period, and the average vegetation cover measure on forest grid over the whole pre-treatment period. We include the last three attributes regardless of the outcome variable under analysis.

Turning to the inference procedure, Abadie et al. (2010) propose to use an exact inferential technique based on placebo tests since large sample techniques are not well-applicable to studies with relatively few treated units. They argue that using a placebo test based technique is appropriate to capture the uncertainty from the fact that we estimate the counterfactual of treated units with a synthetic control. Its first step is to calculate the exact time-specific distribution of the estimated effects in absolute terms[24] by applying the synthetic control method for all units in the donor pool. The second step is to calculate the share of placebo effects that are smaller than the estimated treatment effect from the treated forests, which serves as a significance level of that estimated treatment effect. Abadie et al. (2010) argue that this measure does not take into account the quality of synthetic controls estimated for the potential controls, leading to conservative inferences. They propose the use the ratio of the estimated effects to the corresponding pre-treatment root mean square predictive error to calculate the distribution and the significance levels. In our analysis, we also rely on the results from the normalized test statistics.

5. Results

Columns (1)-(3) of table table D.1 show the monthly-average effects on fire occurrences detected at different confidence levels. Recall that these results

[22] June 2006 is the beginning of the growth season of the agricultural year, while September 2014 is the last period before the program became officially effective.

[23] Forest size might be a relevant determinant of fire occurrences if monitoring by forestry agencies is not proportional. In this case, community members are less likely to be detected and punished for setting fire.

[24] Time-specific in the sense that separate distributions are calculated for each post-treatment period.

are based on the monthly-forest dataset and relies on minimizing the root mean squared prediction errors (RMSPE) in the period from June 2006 until September 2014. The estimates show three patterns.

First, there are large decreases in November (M11 in table table D.1) fire occurrences in the treatment forests after the beginning of the program. This is important since most fires occur in the dry season. More importantly, religious fires, post-harvest fires, and controlled management fires are all lit in November. Turning to the point estimates, average numbers of fires at the grid-level in November 2015, 2016 and 2017 are reduced by, respectively, -0.2, -0.16, -0.11 (col (1)) in response to the program. These suggest an approximately $50\% - 30\%$ reduction compared to the pre-treatment, dry-season fire occurrence in treatment forests (as the average number of fires is about 0.4, see fig. C.5e). However, the effect in 2016 is only significant at 10% level and the effect in 2017 is not significant. This suggests that the marked fall in November fires due to the program is only temporary.

Second, the program seems to reduce fire occurrence in March (M3) as well. Although the absolute size of these effects are smaller (between -0.014 and -0.051), they are still relatively large compared to pre-treatment fires in the pre-rainy, transitory season in the treatment forests ($\approx 0.03 - 0.035$, see fig. C.5f). This March effect is significant up until 2017, suggesting that this is also a transitory effect just as the November effect.

Third, the November effect is consistent regardless of the fire occurrence measure we use, while the March effect is not. Comparing results across columns (4)-(6) all estimated effects are smaller when a higher threshold is chosen for fire detection confidence. Implications on the November and March effects are similar when one introduces a 50% confidence threshold for detection (comparing columns (4) and (5)), but the March effect is not consistent anymore with a 80% confidence threshold. Assuming that the we tend to drop smaller fires when the confidence threshold changes from 50% to 80%, the comparison implies that the March effect is driven by changes in smaller fires.

Comparing the effect sizes on the number fire occurrences (col. (1)-(3)) to those on the share of burned grids (col. (4)-(6)), we find fairly similar impacts. For example, the estimated effect for November 2015 suggests that the share of burned grids decreased by 13.1 percentage points in response to the program (col. (4)), which also sizable given a pre-treatment average of $\approx 20\%$ (see fig. C.6b). Since the relative effect sizes for fire occurrences and for the share of burned grids are similar, these suggest that most of the reduction in fire occurrences are driven by the latter effect. This reflects that either there are fewer fires set on different forest grids or already burning fires spread at a lower rate across forest grids.

One weakness of these estimates is that they partly reflect imperfection in the goodness of fit before the treatment period. We show this for fire occurrence (with no confidence level) in fig. D.7a-D.7b. Before treatment, the synthetic control is below or above the high spikes of forest fire occurrences. For November, the deviation is more consistent as the observed outcomes of the treated forests are always below the synthetic control's. Quantitatively, the pre-treatment RMSPE is .0704, which is rather large even when compared to average pre-treatment fire occurrence in the dry-seasonv (.4). Although imperfect, November treatment estimates corrected with the RMSPE above still yields estimates of $-.1334$, $-.0905$, $-.0395$ for 2015, 2016 and 2017, respectively. In relative terms these suggest a $30-7\%$ reduction compared to average pre-treatment fire occurrence in the dry-season, hence it likely that there is still a November effect. This is not the case for the March effect in which cases the point estimates would become closer to zero.

Finally, we regard the estimated program impacts on vegetation cover in table D.2. Even though the NDVI and EVI measures of vegetation cover are highly correlated, estimates across the two measures are only consistent in that the program does not seem to have a significant impact on dry season vegetation cover (col. (3)-(4)). This is surprising as one would expect more trees staying intact partly as a result of decreasing forest fires in November and of unchanged fire occurrences in the rest of the dry season (Dec.-Febr.). There also seems to be no impact on vegetation cover before the rainy season (col. (5)-(6)) except for 2015 with the EVI as the measure. The effect sizes are similar for the two measures in this year, hence it is not definite whether this effect is significant or not. They would imply a $\approx 18-20\%$ decrease in these measures relative to the pre-treatment average in the pre-rainy transitory period ($\approx 0.16-0.18$, see fig. C.5c). Less clear are the implications from the estimates on post-rainy season measures in col. (1)-(2). Whereas the EVI measure implies no impact, the NDVI measure yields a $\approx 12-13\%$ decrease in 2015 and a $\approx 6\%$ increase in 2016 in response to the program relative to the corresponding pre-treatment mean (≈ 0.35, see fig. C.5a).[25] Unlike the estimates on fire occurrence, these estimates are less likely to be affected by imperfect fitting of the synthetic control in the pre-treatment period. This is visible in fig. D.8 which implies a fairly low

[25]Estimation results with non-imputed vegetation measures are presented in table D.3(see footnote 21). Even though p-values change for some point estimates, point estimates are more or less unchanged.

(.0056) RMSPE.

6. Discussion and further questions

This paper shows that in the short run, the Forest Investment Program program reduced the number of fires at the beginning of the dry-season (November) and at the end of the off-season (March), but these reductions did not clearly translate into more vegetation cover. One possible explanation for this assumes that the avoided fires are small. Small burnings affect low ground vegetation and affects tree cover by killing seeds. Seedlings, that survive because of the lower number of fires, would then need more time to grow and contribute to vegetation density. An alternative, less favourable explanation would be that vegetation saved from the fires are degraded by other channels of deforestation/forest degradation (e.g. grazing, or logging). Following the forests for a longer period and estimating the longer-run effect would be informative on this question.

Also notable that the reductions in fire occurrence are not persistent, but they are only present in two months of the year. Since November and March correspond to the end of the main and the off agricultural season, this fact suggests that most prevented fires might originate from agricultural lands (to clear old fields) and spread to forests. In turn, this would imply that locals either put more effort in controlling these agriculture fires, that local forest management implement more measures to prevent fire spreading, or that there there less agriculture burnings altogether. This explanation does not rule out reduction in other types of fires. Although the sources of each fires are not observable, we can use the geographical locations of the burned grids as an attempt to distinguish between fires spreading from fields around the forests and other types of fires.

Finally, the impact estimates on fire occurrence need to be improved. Even though we argue that the estimations suggest the presence of favourable effect, our results are debatable since the synthetic controls do not match sufficiently closely the outcomes of the treated forests before the program. We expect improvements in our estimates from turning to the augmented synthetic method (Ben-Michael et al., 2018) or the synthetic difference-in-difference method (Arkhangelsky et al., 2018).

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Appendix A. Forest selection criteria

To narrow down the number of forests considered to the program to 23 the following 7 criteria were used:

- Capacity in terms of carbon sequestration of the forest in relation to the productivity
- Level of CO2 emission by wildfire
- Current level of destocking or export of carbon (forest clearing, excessive cutting of firewood, etc.)
- Level of the ecosystems degradation/anthropisation
- Opportunities to take stock of anterior interventions in the forests
- Security level (eliminatory criterion)
- Main factor of deforestation/degradation

From the remaining 23 forests, 12 were selected into the prorgam with the following 8 criteria:

- Forest must have or must be designing a development and management plan
- Opportunity to further develop existing resources (e.g. non-timber products of vegetal and animal origins)
- Spatial span (large forest must be privileged)
- Level of the ecosystems degradation/anthropisation
- How management of common forest areas is allocated (inter-communities and inter-regions)
- Whether the forest is representative in terms deforestation dynamics
- Presence and activity of professional organizations
- Risk level of activating safeguard policies when interventions are done in the forest.

Appendix B. Selected forests

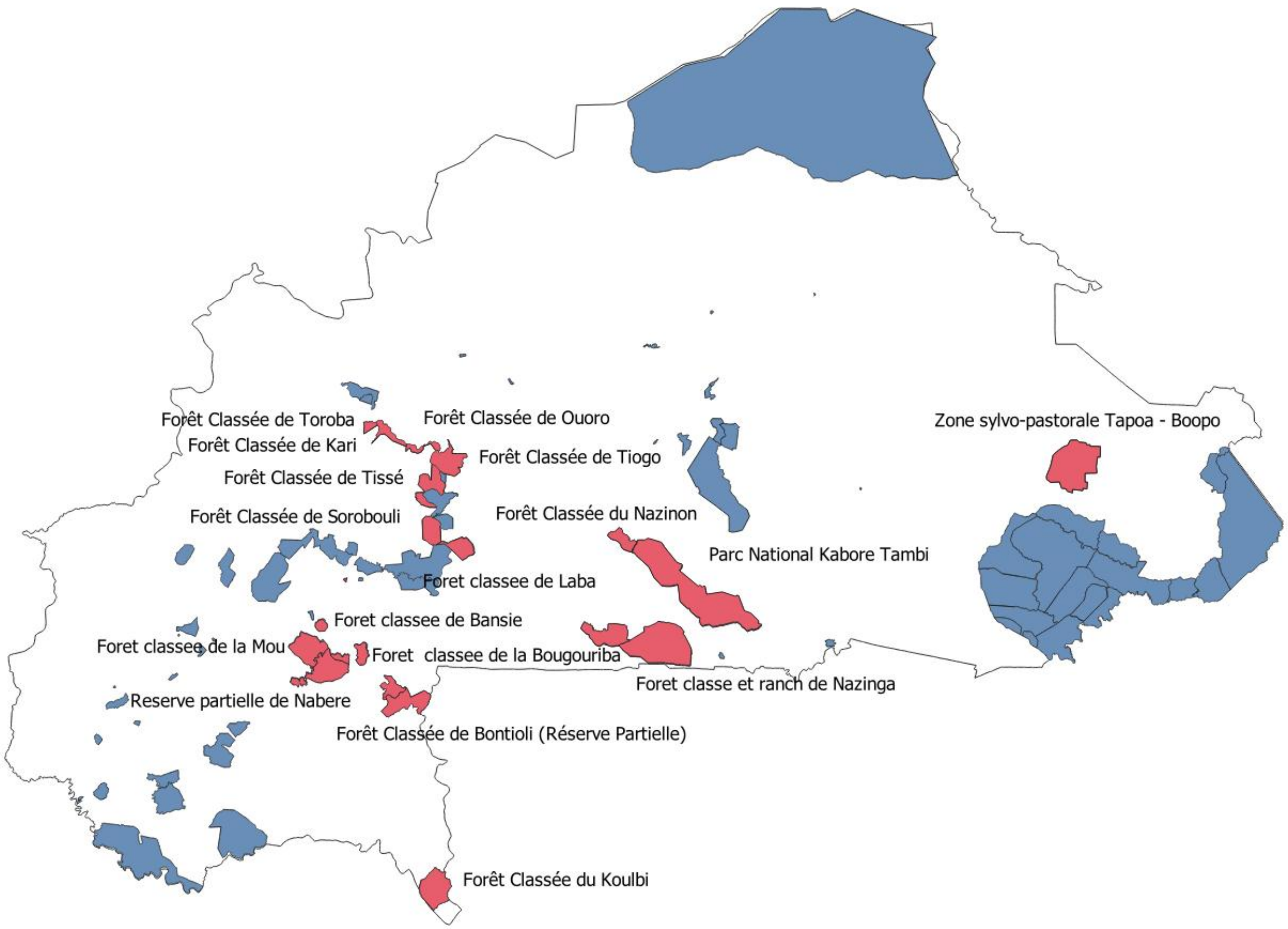
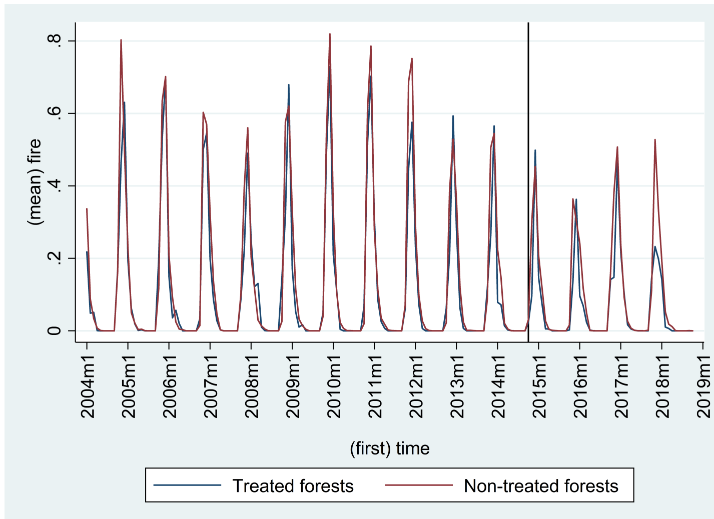
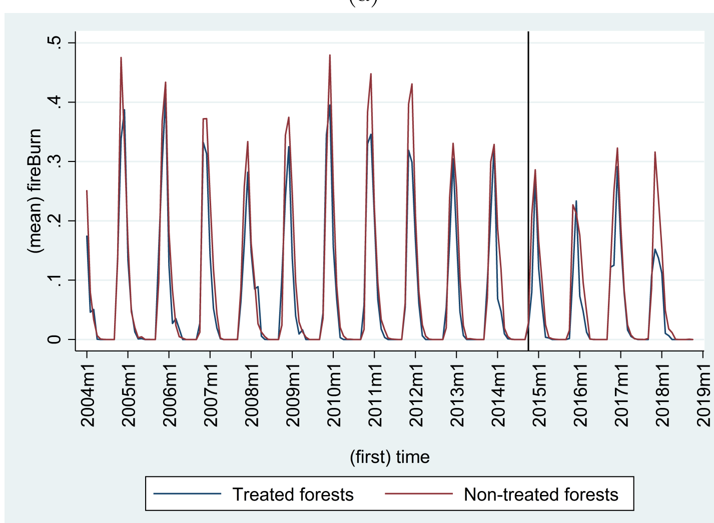


Figure B.1: **Forests in Burkina Faso.** The finally selected 12 forests are highlighted with light red colored with their names. The remaining forests in light blue are the other forests.

Appendix C. Graphs

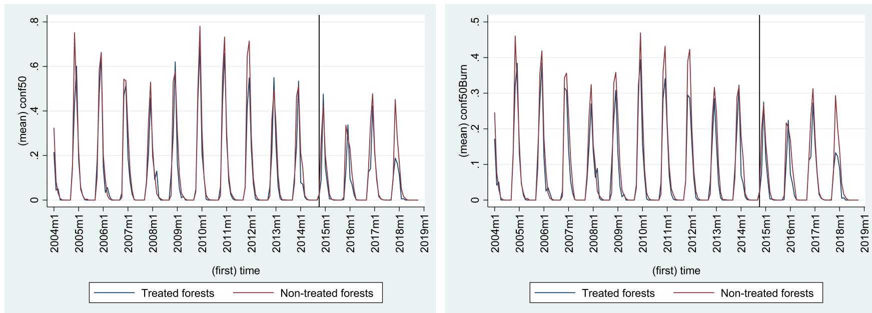


(a)



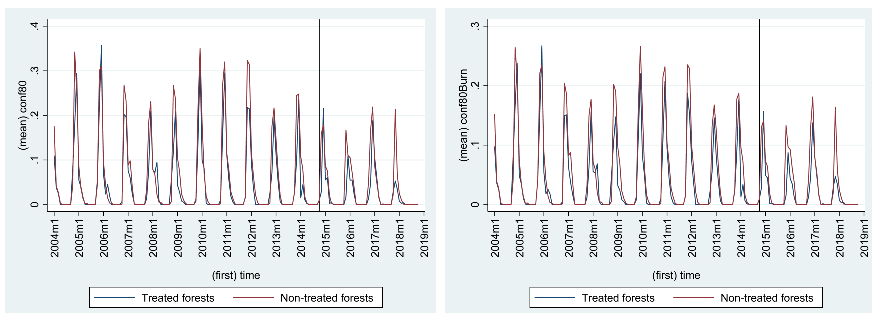
(b)

Figure C.2: Monthly time series of grid-level fire occurrence (a) and share of burned grids (b).



(a) (b)

Figure C.3: Monthly time series of grid-level fire occurrence with at least 50% (a) and the corresponding share of burned grids (b).



(a) (b)

Figure C.4: Monthly time series of grid-level fire occurrence with at least 80% (a) and the corresponding share of burned grids (b).

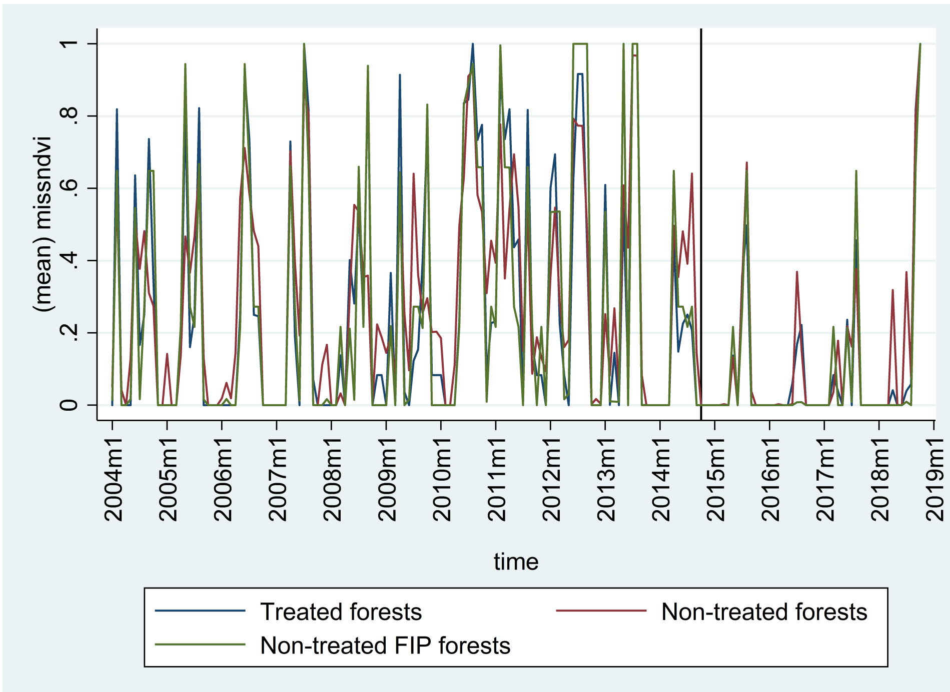
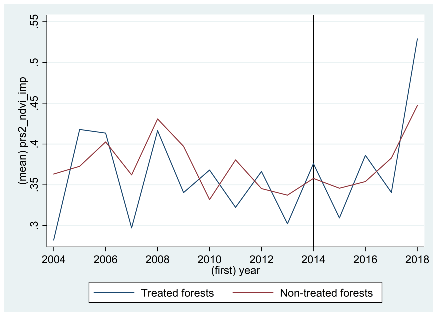
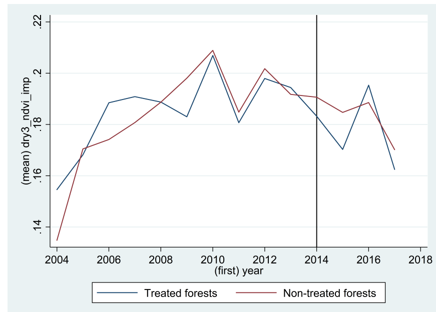


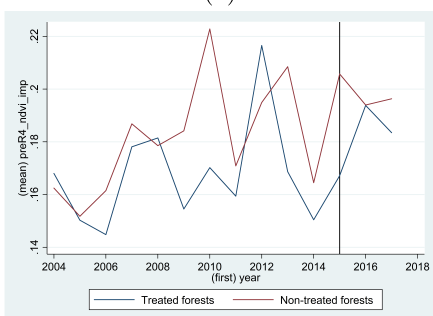
Figure C.5: Time series of the share of forests in the group having missing NDVI for the given month.



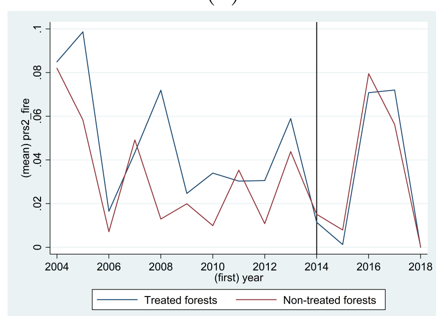
(a)



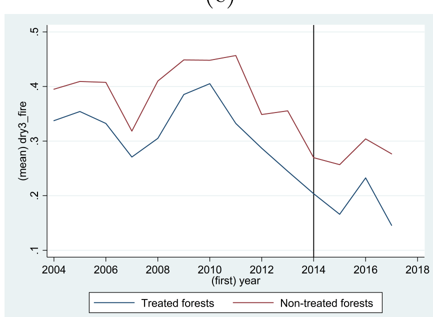
(b)



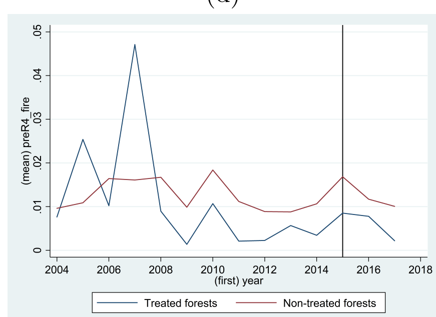
(c)



(d)

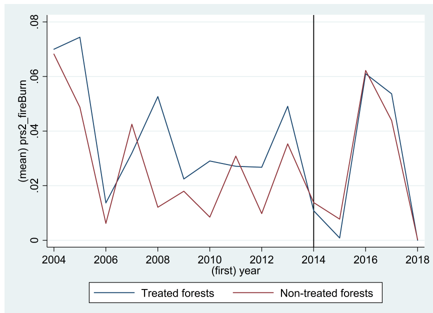


(e)



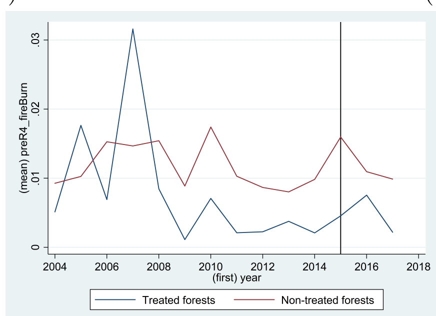
(f)

Figure C.5: Annual forest-level time series capturing specific periods of the agricultural year. Firsts are the averages of ndvi (a) in the post-rainy transitory period (September-October), (b) in the dry season's period (November-February), and (c) in the pre-rainy season transitory period (March-May). Second are the averages of fire occurrence (d) in the post-rainy transitory period (September-October), (e) in the dry season's period (November-February), and (f) in the pre-rainy season transitory period (March-May). Third are the averages of the share of burned grids in the (g) post-rainy transitory period (September-October), and (h) in the dry season (November-February).



(a)

(b)



(c)

Figure C.6: Annual forest-level time series capturing specific periods of the agricultural year. Time series show the averages of the share of burned grids in the (a) post-rainy transitory period (September-October), (b) in the dry season (November-February), and (c) in the pre-rainy season (March-May).

Appendix D. Estimation results from the synthetic control method

Month	Year	(1) Fire	(2) Fire c50	(3) Fire c80	(4) Share of burned grids	(5) Share of burned grids(c50)	(6) Share of burned grids(c80)
M1	2015	0.0408	0.0166	0.0099	0.0399	0.0139	0.0063
		[0.4103]	[0.604]	[0.8612]	[0.4229]	[0.7552]	[0.9746]
	2016	-0.0764*	-0.0502	-0.0514	-0.0696*	-0.0364	-0.053
		[0.0771]	[0.317]	[0.7187]	[0.0652]	[0.3613]	[0.6607]
	2017	0.037	0.0469	0.0626	0.0006	0.0056	0.039
		[0.6127]	[0.6845]	[0.1848]	[0.9321]	[0.9]	[0.2438]
	2018	0.0004	0.0023	0.004***	-0.0007	0.0029	0.0039***
		[0.3692]	[0.345]	[0.0002]	[0.7319]	[0.4827]	[0.0007]
M2	2015	0.0053	0.008	0.0175	-0.0009	0.0068	0.0038
		[0.8856]	[0.9908]	[0.481]	[0.977]	[0.8288]	[0.6676]
	2016	-0.0008	-0.0068	0.0247	-0.0052	-0.0017	0.0051
		[0.6517]	[0.7633]	[0.4044]	[0.7511]	[0.7469]	[0.6831]
	2017	0.0186	0.0223	0.016	-0.0031	0.0108	0.0113

		[0.1332]	[0.1698]	[0.2416]	[0.7696]	[0.476]	[0.3175]
	2018	-0.0559***	-0.0762***	-0.0162	-0.055***	-0.0738***	-0.0144
		[0.0001]	[0.0]	[0.1691]	[0.0023]	[0.0014]	[0.2167]
M3	2015	-0.0148*	-0.0199**	-0.0036	-0.0164	-0.0194	-0.0034
		[0.0588]	[0.0484]	[0.5808]	[0.1314]	[0.1314]	[0.5965]
	2016	-0.0243***	-0.0162***	-0.0074	-0.0345***	-0.0255**	-0.014
		[0.0012]	[0.0054]	[0.9483]	[0.0014]	[0.0129]	[0.8159]
	2017	-0.051***	-0.0327***	-0.0094	-0.0503***	-0.0327***	-0.0082
		[0.0001]	[0.0001]	[0.2042]	[0.0002]	[0.0002]	[0.2385]
	2018	0.0004	0.0023	0.004***	-0.0007	0.0029	0.0039***
		[0.3692]	[0.345]	[0.0002]	[0.7319]	[0.4827]	[0.0007]
M4	2015	0.0036	0.0036	0.0042**	0.0009	0.0015	0.0016
		[0.4242]	[0.382]	[0.0475]	[0.7453]	[0.6978]	[0.2067]
	2016	0.002***	0.002***	0.0021***	0.001***	0.001***	0.0011***
		[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]
	2017	0.0041	0.0042	-0.0001	0.0041	0.0043	-0.0003
		[0.5335]	[0.5505]	[0.835]	[0.6268]	[0.6444]	[0.8358]
	2018	-0.0006	-0.0003	-0.0001	-0.0008	-0.0002	-0.0002
		[0.8938]	[0.9316]	[0.835]	[0.8829]	[0.9349]	[0.8358]
M5	2015	-0.0002	-0.0002	-0.0011	-0.0001	-0.0002	-0.0006
		[0.5149]	[0.4668]	[0.5671]	[0.638]	[0.4908]	[0.5481]
	2016	-0.0002	0.0	0.0	-0.0001	0.0	0.0
		[0.2522]	[1.0]	[1.0]	[0.3283]	[1.0]	[1.0]
	2017	0.0014	0.0011	0.0016***	0.0014	0.0011	0.0016***
		[0.7073]	[0.89]	[0.0]	[0.4742]	[0.7097]	[0.0]
	2018	-0.0001	-0.0	-0.0	-0.0001	-0.0	-0.0001
		[0.8522]	[0.9267]	[0.835]	[0.8831]	[0.9032]	[0.8358]

For June, July, August and September, all effect estimates are 0 and the corresponding p-values are 1.

M10	2014	0.0006	-0.0009	-0.0026	-0.0036	-0.0015	-0.0027
		[0.6684]	[0.9854]	[0.3193]	[0.8432]	[0.9902]	[0.2698]
	2015	-0.0034	-0.002	-0.0003	-0.0063	-0.0026	-0.0005
		[0.8877]	[0.9121]	[0.854]	[0.4984]	[0.7987]	[0.7225]
	2016	-0.0343	-0.045	-0.0506	-0.0423	-0.0327	-0.0452
		[0.9455]	[0.6002]	[0.1146]	[0.7781]	[0.6634]	[0.1043]
	2017	0.0024	-0.0157	0.0032	-0.0085	-0.0134	0.0089
		[0.8213]	[0.7166]	[0.8726]	[0.8129]	[0.5694]	[0.7578]
M11	2014	-0.1398	-0.1014	-0.0707*	-0.1031	-0.0752	-0.0561**
		[0.302]	[0.352]	[0.0831]	[0.2025]	[0.2881]	[0.0444]
	2015	-0.2009**	-0.1772***	-0.1036***	-0.1316***	-0.107***	-0.0826***
		[0.0121]	[0.0015]	[0.0002]	[0.0071]	[0.0032]	[0.0004]
	2016	-0.1646*	-0.1519***	-0.0637*	-0.0977**	-0.0668*	-0.0371
		[0.0508]	[0.0092]	[0.0771]	[0.0423]	[0.0507]	[0.1337]
	2017	-0.1104	-0.1113	-0.0661	-0.0797	-0.0503	-0.0319
		[0.2711]	[0.1041]	[0.1045]	[0.1452]	[0.2118]	[0.1979]
M12	2014	0.1275	0.1198	0.0239	0.0392	0.0494	-0.0027
		[0.4295]	[0.402]	[0.9256]	[0.5577]	[0.4546]	[0.665]
	2015	0.1277	0.1161	0.05	0.0685	0.0386	0.0371
		[0.7104]	[0.7084]	[0.3544]	[0.7544]	[0.8573]	[0.4449]
	2016	0.0962	0.0877	-0.0056	0.0519	0.0432	-0.0341
		[0.3591]	[0.4786]	[0.447]	[0.4179]	[0.4628]	[0.1622]
	2017	0.0184	0.0405	0.009	0.0013	0.0151	0.0085
		[0.6872]	[0.4415]	[0.4176]	[0.8201]	[0.3481]	[0.4272]

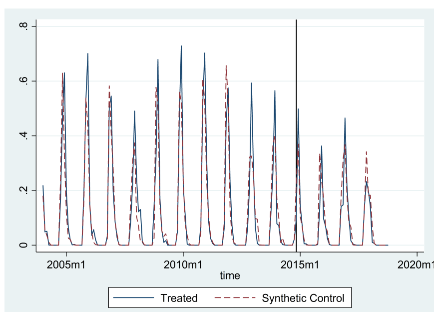
Table D.1: **Estimated average treatment effect on the FIP participant forests from the synthetic control method.** Estimates are based on foret-month-level data. Treatment starts October 2014. P-values from placebo analysis are in parentheses. P-values standardized with pre-treatment RMSPE are in square brackets. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	NDVI_imp	EVI_imp	NDVI_imp	EVI_imp	NDVI_imp	EVI_imp
	PRS2 (Sep-Oct)		DRY3 (Nov-Feb)		PRER4 (March-May)	
2015	-.0468*	-.0087	-.0121	-.0089	-.0293	-.03385**
	[.0111]	[.5160]	[.1245]	[.4065]	[.1722]	[.0351]
2016	.0239**	.0076	-.0139	-.0040	.0018	.0007
	[.0396]	[.4744]	[.1766]	[.8711]	[.583]	[.8773]
2017	-.0013	.0009	.0023	-.0007	-.0103	-.0133
	[.7975]	[.6371]	[.1875]	[.3681]	[.7709]	[.3533]

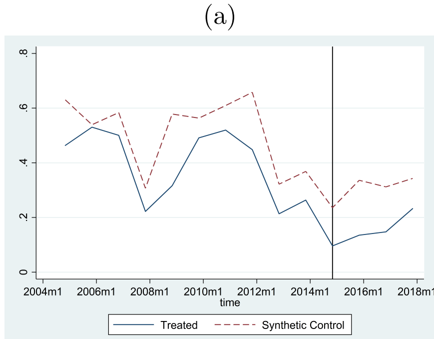
Table D.2: **Estimated average treatment on the treated effects on vegetation cover from the synthetic control method.** Estimates are based on annual forest-level data. Treatment starts from 2014 for the dry-season variables (`dry3_ndvi_imp` and `dry3_evi_imp`) and pre-rainy transitory period variables (`preR4_ndvi_imp` and `preR4_evi_imp`), and from 2015 for the post-rainy transitory period variables (`prs2_ndvi_imp` and `prs2_evi_imp`). P-values from placebo analysis are in parentheses. P-values standardized with pre-treatment RMSPE are in square brackets. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	NDVI	EVI	NDVI	EVI
	DRY3 (Nov-Feb)		PRER4 (March-May)	
2015	-.0110	-.0096	-.0144	-.0358***
	[.4466]	[.3437]	[.1707]	[.0016]
2016	-.0160*	-.0048	.00751	.0090
	[.0957]	[.9182]	[.4472]	[.4802]
2017	.0034**	-.0013	.-.0028	-.0083
	[.0299]	[.2531]	[.8147]	[.5566]

Table D.3: **Estimated average treatment on the treated effects on vegetation cover from the synthetic control method.** Estimates are based on annual forest-level data. Treatment starts from 2014 for the dry-season variables (`dry3_ndvi` and `dry3_evi`) and pre-rainy transitory period variables (`preR4_ndvi` and `preR4_evi`). Forests with missing values from the time series are dropped from the analysis. Estimations with the post-rainy season variables are dropped from the same reason. P-values from placebo analysis are in parentheses. P-values standardized with pre-treatment RMSPE are in square brackets. *** p<0.01, ** p<0.05, * p<0.1.



(a)



(b)

Figure D.7: Monthly time-series of fire occurrence (`fire`) in the treatment and the estimated synthetic control. Figure (a) shows the estimates covering all months while figure (b) shows the estimates for Novembers only. The corresponding pre-treatment root mean squared prediction error is .07045076.

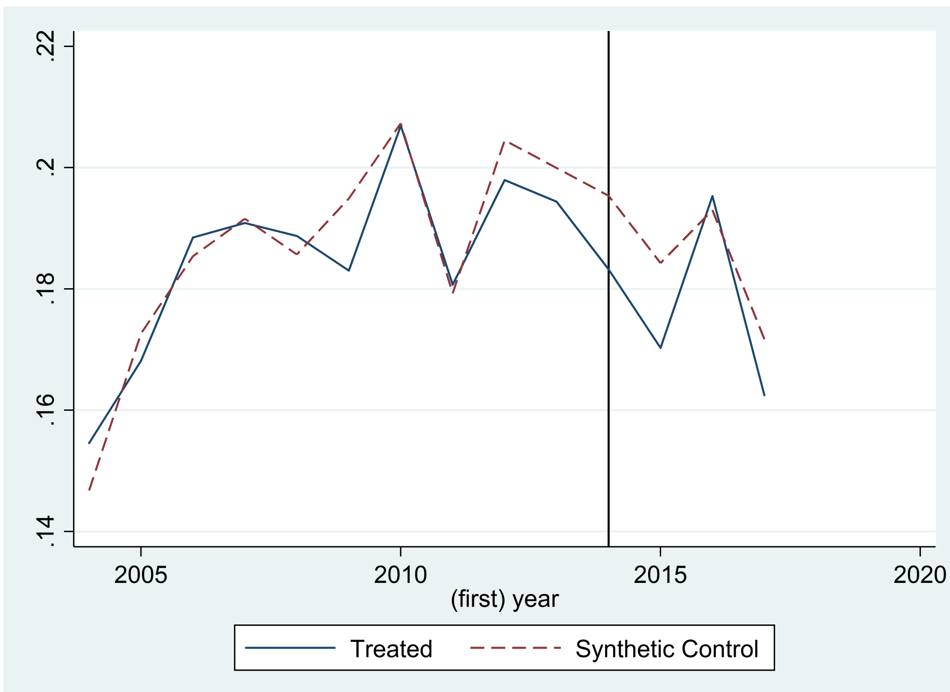


Figure D.8: Annual time series of dry-season vegetation cover measured with NDVI (`dry3_ndvi_imp`) in the treatment forest and the estimated synthetic control. The corresponding pre-treatment root mean squared prediction error is .00563849.